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Modeling the Human Memory in Nerve Fields

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Abstruct

This paper describes the modeling of human memory using a nerve field model which is proposed for modeling the mechanism of brain mathmatically. In our model, two phases of memory, retention and recollection, are focused on. The former consists of two stages, short-term memory (STM) and long-term memory (LTM). The proposed model consists of three parts, the STM Layer, LTM Layer and the Intermediate Layer between them. Each of these is constructed by a nerve field. In the STM Layer, memorized information is retained dynamically in the form of the reverberating states of units within the layer, while in the LTM Layer, it is stored statically in the form of structures of the weight on the links between units. the Intermediate Layer is introduced to translate this dynamic representation in the STM Layer to the LTM Layer, and also to extract the static information from the STM Layer. In addition to this, we consider the recollection of information stored in the LTM. Finally, the behavior of this model is demonstrated by computer simulation.

1. Introduction

Many studies on memory model have been carried out over a long period of time. In recent years it has become necessary to realize the memory model which can treat information flexibly in the same way as human memory. One of the most popular approaches to constructing such memory models adopts the Parallel Distributed Processing (PDP) models[1) 2)]. Some of these are categorized as neural network models[3) 4)].

Nerve field theory[5)] is also one such models proposed for the modeling of the mechanism of the brain mathematically. It is well known that this model can treat the pattern dynamics of neurons. The temporal retention of information, called short-term memory (STM), is one important feature of this model. However, there is another type of information retention which is known as called long-term memory (LTM). That is to say, information extracted from the dynamic state of the STM is stored in a static state in the LTM. In general, only latter type of memory retention is dealt with in most of the memory models using a connectionist approach. There, the information is stored in the form of connections between units.

In this paper we construct a memory model[6)] using a nerve field model. In our model, STM and LTM are uniformly described by the dynamics of the nerve field model. That is, the STM is realized by the reverberation of the state of units, and the LTM by the structure formed by changes of the weights on the connections between units. It may be possible to expand our model to one in which the interaction between an incoming information and the information already existing in LTM is represented in the STM. This is regarded as the reconstruction of memory.

In addition, we consider the recollection of the information stored in the LTM. This is an essential function of memory enableing it to use the memorized information for other important functions of brain, such as recogniton, voluntary behavior, and so on. Finally, the results of the computer simulations on this model are shown.

2. Nerve Field Model

The nerve field model is an artificial neural network model, in which the set of nerve units is regarded as spatially continuous. The dynamics of the model are described by Amari as follows[5)]:

Suppose an m-layer nerve field. Let $u_i(\boldsymbol{x}, t)$ be the state of a unit at place $\boldsymbol{x}$ at time t on the i-th layer. The dynamics of the state of the unit are characterized by the following equations:

$$\begin{aligned} \tau_i \frac{\partial u_i(\boldsymbol{x},t)}{\partial t} &= -u_i(\boldsymbol{x},t) \\ &\quad + \sum_{j=1}^{m} \int w_{ij}(\boldsymbol{x},\boldsymbol{x}') z_j(\boldsymbol{x}') d\boldsymbol{x}' \\ &\quad + s_i(\boldsymbol{x},t) - h_i, \qquad (1) \\ &\quad i = 1, \ldots, m. \\ z_i(\boldsymbol{x}) &= f_i(u_i(\boldsymbol{x})). \qquad (2) \end{aligned}$$

Here, τ_i is the time constant for the dynamics of each unit in the i-th layer, h_i is its threshold value and $s_i(\boldsymbol{x}, t)$ are the external inputs to a unit in the i-th layer at place $\boldsymbol{x}$. $w_{ij}(\boldsymbol{x}, \boldsymbol{x}')$ is a weighting function that gives the intensity of a connection from a unit in the j-th layer at place $\boldsymbol{x}'$ to a unit in the i-th layer at place $\boldsymbol{x}$. $f_i(\boldsymbol{x})$ is the output function of a unit in the i-th layer at place $\boldsymbol{x}$ and $z_i(\boldsymbol{x})$ is its output.

This nerve field model is particularly suitable for both types of memory retention, STM and LTM. This is because it can deal with spatiotemporal patterns and form a permanent structure proportional to the input patterns out of a homogeneous field.

3. Memory Model

Our model consists of three parts, the STM Layer, LTM Layer and the Intermediate Layer for translation from the former to the latter. The information retained in this model is represented by patterns composed of points in the field.

First, the pattern to be stored is presented to the STM Layer and retained in a form of the reverberation. This refers to the ripple effect outwards from the points in the patterns. The reverberation, once evoked by the presentation of a pattern, propagates in the field persistently even after the pattern vanished.

In the LTM Layer, on the other hand, the pattern is retained statically as a structure formed by the changes of weights on the connections within the layer.

Here, a problem arises in the transmission from the STM Layer to the LTM Layer. Because in the STM Layer information is retained distributively and dynamically, it is impossible to store it in LTM in the same form. To translate this information, an Intermediate Layer is inserted between the two layers. It is in this Intermediate Layer, that a presented pattern is extracted from the reverberation in the STM Layer, and given to the LTM Layer.

The structures and the weighting functions of these three layers are described in the subsections below.

3.1 STM Layer

To realize the STM retention mentioned above, the STM Layer is composed of two sublayers. One consists of excitatory units (F_S layer) and the other consists of inhibitory units (F_H layer). Their dynamics are as follows:

$$\begin{aligned} \tau_S \frac{\partial u_S(\boldsymbol{x},t)}{\partial t} &= -u_S(\boldsymbol{x},t) \\ &\quad + \int_{F_S} w_{SS}(\boldsymbol{x},\boldsymbol{x}') 1[u_S(\boldsymbol{x}',t)] d\boldsymbol{x}' \\ &\quad + \int_{F_H} w_{SH}(\boldsymbol{x},\boldsymbol{x}') 1[u_H(\boldsymbol{x}',t)] d\boldsymbol{x}' \\ &\quad + s_S(\boldsymbol{x},t) - h_S, \qquad (3) \\ \tau_H \frac{\partial u_H(\boldsymbol{x},t)}{\partial t} &= -u_H(\boldsymbol{x},t) + w_{HS} 1[u_S(\boldsymbol{x},t)] \\ &\quad - h_H. \qquad (4) \end{aligned}$$

Here, w_{HS} is the weight on the connection from a unit in the F_S layer to one in the F_H layer, w_{SS} is the weighting function in the F_S layer (eq.(5)), and w_{SH} is the one from the F_H layer to the F_S layer (eq.(6)).

$$\begin{aligned} w_{SS}(\boldsymbol{x},\boldsymbol{x}') &= A_S \exp\left(\frac{-|\boldsymbol{x}-\boldsymbol{x}'|^2}{\sigma_S^2}\right), \qquad (5) \\ w_{SH}(\boldsymbol{x},\boldsymbol{x}') &= -A_H \exp\left(\frac{-|\boldsymbol{x}-\boldsymbol{x}'|^2}{\sigma_H^2}\right). \qquad (6) \end{aligned}$$

3.2 Intermediate Layer

This layer extracts the center of each reverberating region by lateral-inhibition type connections between the STM Layer and itself.

$$\begin{aligned} \tau_M \frac{\partial u_M(\boldsymbol{x},t)}{\partial t} &= -u_M(\boldsymbol{x},t) \\ &\quad + \int_{F_S} w_{MS}(\boldsymbol{x},\boldsymbol{x}') 1[u_S(\boldsymbol{x}',t)] d\boldsymbol{x}' \\ &\quad - h_M, \qquad (7) \end{aligned}$$

$$w_{MS}(\boldsymbol{x},\boldsymbol{x}') = \left(1 - \frac{|\boldsymbol{x}-\boldsymbol{x}'|^2}{\sigma_M^2}\right) \exp\left(\frac{-\alpha_M^2 |\boldsymbol{x}-\boldsymbol{x}'|^2}{\sigma_M^2}\right), \quad (8)$$

where σ_M is the coefficient with respect to the spread of connecting region, and α_M is concerned with the strength of excitatory and inhibitory connections.

3.3 LTM Layer

The connection in the LTM Layer (F_L layer) is modified according to the following equations (10-12), and then the structure that retains the pattern is formed in two types of connections. One is a local type of between the neighbors of each point in a pattern, and the other is a network type between all the points of a pattern.

$$\begin{aligned}\tau_L \frac{\partial u_L(\boldsymbol{x},t)}{\partial t} &= -u_L(\boldsymbol{x},t) \\ &\quad + \int_{F_M} w_{LM}(\boldsymbol{x},\boldsymbol{x}')1[u_M(\boldsymbol{x}',t)]d\boldsymbol{x}' \\ &\quad + \int_{F_L} w_{LL}(\boldsymbol{x},\boldsymbol{x}')1[u_L(\boldsymbol{x}',t)]d\boldsymbol{x}' \\ &\quad + s_L(\boldsymbol{x},t) - h_L \ , \qquad (9)\end{aligned}$$

$$w_{LM}(\boldsymbol{x},\boldsymbol{x}') = \left(1 - \frac{|\boldsymbol{x}-\boldsymbol{x}'|^2}{\sigma_{LM}^2}\right)\exp\left(\frac{-\alpha_{LM}^2|\boldsymbol{x}-\boldsymbol{x}'|^2}{\sigma_{LM}^2}\right) . \qquad (10)$$

$$\frac{\partial w_{LL}(\boldsymbol{x},\boldsymbol{x}')}{\partial t} = \epsilon 1[s(\boldsymbol{x})](s(\boldsymbol{x})s(\boldsymbol{x}') - w_{LL}(\boldsymbol{x},\boldsymbol{x}')) \ , \qquad (11)$$

$$s(\boldsymbol{x}) = \int_{F_M} w_{LM}(\boldsymbol{x},\boldsymbol{x}')1[u_M(\boldsymbol{x}',t)]d\boldsymbol{x}' \ . \qquad (12)$$

Where ϵ is the coefficient of the learning rate.

Moreover, the stored information is recollected from this layer autoassociatively. That is, a stored pattern is retrieved correctly from only a part of, or a similar pattern to the one stored.

4. Simulations

Some experiments were carried out to show the performance of this model. The results are as follows:

4.1 STM Layer

This experiment shows the retention of a presented pattern in the STM Layer. We used two dimensional nerve fields discretized by 80×80 units, with the parameters set as follows: $\tau_S = 1.0$, $\tau_H = 1.0$, $h_S = 0.5$, $h_H = 0.5$, $A_S = 0.13$, $A_H = 1.6$, $\sigma_S = 1.0$, $\sigma_H = 3.0$, $w_{HS} = 1.0$.

The input pattern consisting of three points was presented to the F_S layer only at $t = 0$. These points were retained as a reverberating state in the F_S layer as shown in Fig.1.

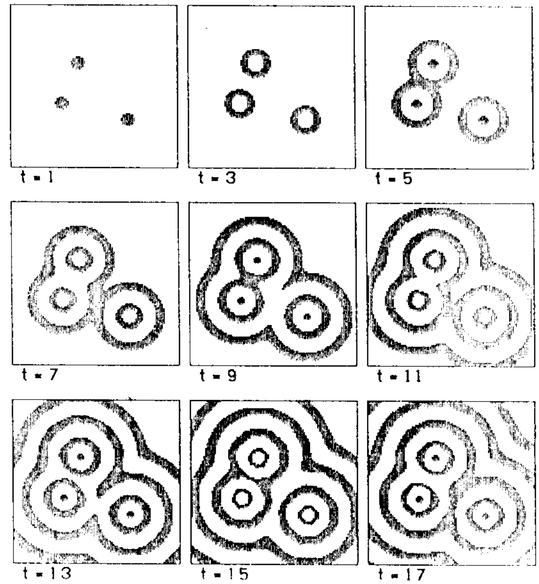


Fig.1 The Reverberation in the STM Layer

4.2 Intermediate Layer

To observe the extraction of the center of the reveberating region, we employed a one dimensional nerve field consisting of 75 units. The parameters were as follows: $\tau_M = 1.0$, $h_M = 0$, $\sigma_M = 0.8$, $\alpha_M = 0.6$.

Fig.2(a) is the reverberation on the STM Layer, Fig.2(b) is the state of units in the Intermediate Layer, and Fig.2(c) is the output from this layer. The localized excitation shown in Fig.2(c) corresponds to the point which is the component of the presented pattern in the STM Layer.

On the other hand, as shown in Fig.2(d-f), there is no excited state of units on the boundary of the two reverbarating regions.

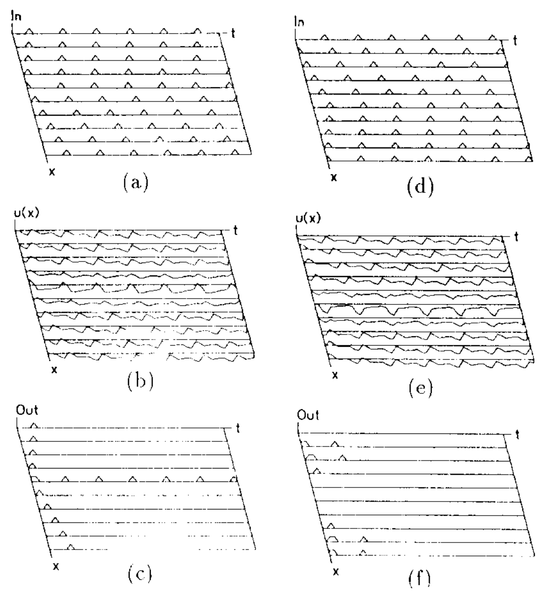


Fig.2 The Extraction by Intermediate Layer

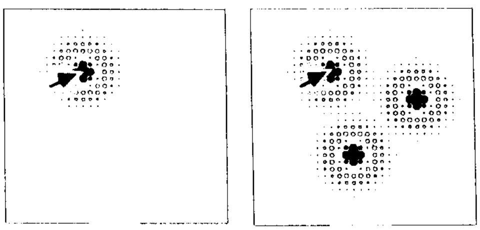
From these figures, we see that the presented pattern is extracted by this Intermediate Layer.

4.3 LTM Layer

The nerve fields were two dimensional fields of 30×30 units, and the parameters were: $\tau_L = 1.0$, $h_L = 0$, $\epsilon = 0.2$, $\sigma_{LM} = 2.0$, $\alpha_{LM} = 0.8$.

In this experiment, the pattern to be stored consisted of three points. These points were retained in the structure formed by the weights on the connection between the units all over the field. The weights on the connections from the unit pointed to by the arrow to all the units in the field are shown in Fig.3. In these figures, ● represents positive weights and ○ represents negative ones. Here, the diameter of a circle is propotional to the magnitude of the weight.

Fig.3(a) shows the initial state, and after memorizing the pattern, the weights were changed as Fig.3(b). Thus, these figures show that the structure corresponding to the presented pattern has been formed.

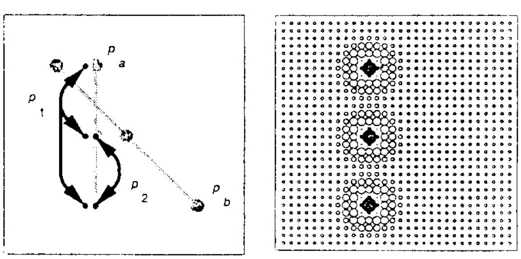


(a) (b)

Fig.3 The Formation of Structure in the LTM Layer

4.4 Recollection

The parameters of the LTM Layer are the same as above. Two patterns shown in Fig4(a), p_a and p_b, were retaind in the LTM Layer simultaneously. Fig.4(b) shows that the stored pattern p_a can be correctly recollected from either key pattern represented in Fig.4(a); p_1 is similar to p_a, and p_2 is a part of p_a.



(a) (b)

Fig.4 The Recollection in the LTM Layer

5. Conclusion

We have described the modeling of memory in the nerve field model. The proposed model deals with the two phases of memory, the retention and recollection of information. In particular, two different types of memory retention, STM and LTM have been uniformly represented by the dynamics of the nerve fields. This property will be of great importance when we consider the interaction between the memory resources which have already been stored and those which may be newly memorized. Work on this problem, which is the reconstruction of memory or the higher processing of memory resources, will follow.

In this paper, we constructed the framework of a memory model based on the dynamics of nerve fields, and verified it by the following computer simulations:

(1) The retention of patterns in the form of a reverberation in the STM Layer.

(2) The extraction of the input points from the reverberating regions in the Intermediate Layer.

(3) The formation of the structure in the LTM Layer

(4) The recollection of the patterns from the LTM Layer autoassociatively.

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